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The determinants of students' return intentions: A partial proportional odds model

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Abstract

This paper examines the determinants of foreign students' nonreturn intention to their home countries following completion of their study abroad. Such students' nonreturn is a type of brain drain. Survey data on the return intention of foreign students studying in tertiary-level courses in New Zealand universities are analyzed using a partial proportional odds model. This model takes into account the ordinal nature of the return intention as the dependent variable while at the same time allowing for possible violation of the parallel lines assumption from the explanatory variables. Perceptions of different aspects of one's home country, particularly the aspect of skill use opportunities, are generally found to have larger impacts on return intention than demographic, education-related, and sociocultural-related factors. Based on the results, the paper discusses some relevant policy implications.

Keywords: foreign students' nonreturn/migration, brain drain, partial proportional odds model, return intention

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1 Introduction

New Zealand is an emerging player in the provision of international education. In 2000/2001, there were only 8,210 foreign students in New Zealand, but the number increased to 33,047 in 2007 (UNESCO 2003, 2009). In the Asia-Pacific region, New Zealand is currently ranked third after Australia and Japan as the most popular destination country for international education. New Zealand is among the top five most popular destination countries among students from certain Asian countries and small Pacific island countries (UNESCO 2009).

The main sending countries of foreign students to New Zealand are China, South Korea, Japan and India. In terms of the number of student permits or visas issued as shown in Figure 1, these Asian countries send the highest volume of students to New Zealand. The sharp increase in the number of permits/visas issued to the Chinese students is due to the low value of the New Zealand currency, whereas the rapid decline is because of the greater competition for Chinese students from other countries such as Australia, the U.S., and Canada (Ministry of Education 2009). The trends shown in Figure 1 include foreign students at all levels, i.e., high school students, English language learners, polytechnic and university students.

In a recent report by the New Zealand Department of Labour (Merwood 2007), it is estimated that 27 percent of the foreign students who began their studies in the 1999/00 and 2000/01 cohorts (with a combined total of approximately 47,000 foreign students) have continued to stay on in New Zealand after completing their studies, either for work and/or residence purposes. Again, the reported figures do not differentiate between university-level foreign students from those of non university-level.

This paper looks at the determinants of the return intention of foreign students currently studying in New Zealand universities. The focus is on university-level students (i.e., at the Bachelor, Masters or doctoral degree level) because if such highly educated students do not intend to return to their home countries, their nonreturn or migration may contribute to the brain drain phenomenon.

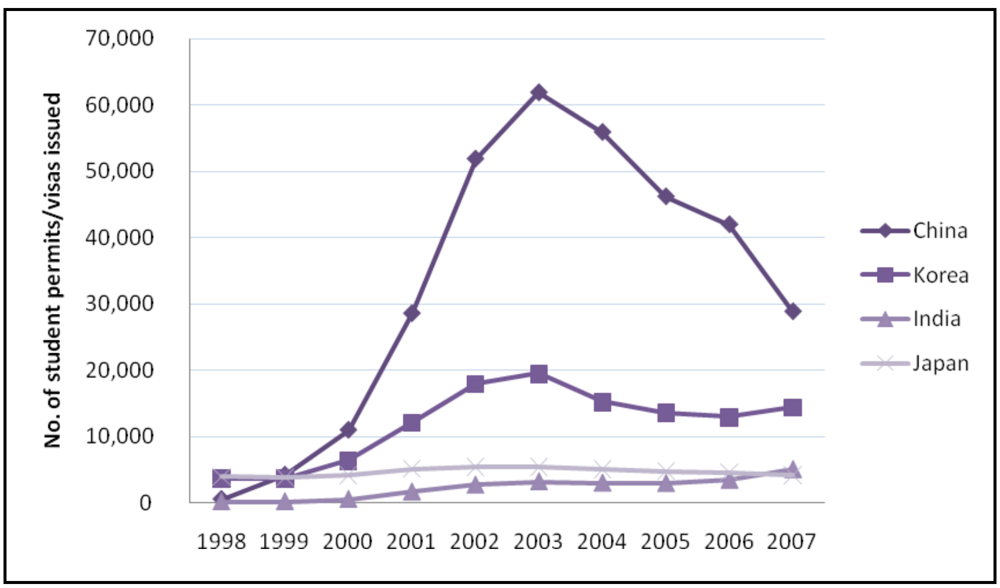

Figure 1. Number of student permits/visas issued
(Source: New Zealand Department of Immigration)

Apart from Soon (2008, 2009), there is a lack of empirical studies on the issue of university-level foreign students' nonreturn in New Zealand. There are a handful of empirical studies on professional brain drain into New Zealand but not on foreign students' nonreturn specifically (Brown and Connell 2004; Gani and Ward 1995). There is a large volume of empirical work focusing on the nonreturn of foreign students studying in the United States and quite a number of these studies examine specifically the return intention of such students (Gungor and Tansel 2008; Baruch et al. 2007; Hazen and Alberts 2006; Alberts and Hazen 2005; Zweig 1997; Jayme 1982; Kao and Lee 1973). Empirical studies on the return intention of foreign students in countries other than the U.S. are relatively few. For example, Li et al. (1996) examine the return intention of foreign students in the U.K., while a somewhat dated study by Rao (1979) examines the return intention of foreign students in Australia.

Of these studies that explicitly model the probability of students' return intention, they use discrete choice models such as the simple logit (Li et al. 1996; Soon 2008), ordered probit (Gungor and Tansel 2008), and the multinomial logit model (Zweig 1997; Soon 2009). In general, most studies on students' return intention conclude that students studying abroad do not intend to return home, mostly citing amongst others, better opportunities for professional advancement and better work environment abroad. From the literature, it appears that the use of discrete choice models is a widely accepted approach to model return intention at the individual level.

The U.S. by far has the most comprehensive macro-level data compilation and such compilation has enabled studies on the rates of foreign students' nonreturn in the U.S. (Bratsberg 1995; Huang 1988). These studies use the rate of visa status adjustments (from student to permanent resident status) to proxy the rate of foreign students' nonreturn. Therefore, such nonreturn rates can be regarded as referring to actual nonreturn as opposed to intended nonreturn.

In New Zealand's case, although New Zealand's Department of Labour/Immigration compiles data on the number of foreign students' permits issued and the number of work/residence permits issued for each year-cohort of students, the figures are not disaggregated by level of studies. The figures therefore do not permit estimation on the nonreturn rates of tertiary-level students. There is also no readily available individual-level dataset. Individual-level data on foreign students are compiled separately by each of the eight universities in New Zealand. However, such data are not released on grounds of confidentiality, even for academic research purposes.

Due to the lack of an ideal dataset, this paper turns to the use of individual-level intention data. The data for this paper are collected through an online survey sent out to the foreign students studying in New Zealand's University of Otago and University of Canterbury. These two universities are the only two universities, out of eight, that have agreed to let their foreign students participate in the survey.

Soon (2008) examines the determinants of return intention using a simple logit model. The model lacks richness in information as it dichotomizes the respondents' intentions. The current paper improves on this by separating the dichotomous responses into four categories using a partial proportional odds model. This can reveal more information with respect to how strong one's return intention is. The use of this model is the paper's point of departure from the students' nonreturn literature, in which, either an ordered probit (Gungor and Tansel 2008) or a multinomial logit model (Zweig 1997) is usually adopted.[1] There are yet to be empirical studies on the issue of students' nonreturn

[1] The model specification section offers a brief comparison between the performance of a partial proportional odds, an ordered logit, and a multinomial logit model.

using this model although it has been applied extensively in medical and health-related literature (Ananth and Kleinbaum 1997; Bender and Grouven 1998; Lall et al. 2002; Peterson and Harrell 1990).

Section 2 gives an overview of the data. Section 3 sets up the partial proportional odds model, followed by results and discussions in Section 4. Section 5 checks for model specification and robustness. The final section concludes with some relevant policy implications.

2 Data and summary statistics

Individual level data are used in this study. These data are obtained through an online questionnaire survey conducted between March and May 2008. There were 512 respondents from Otago and 269 from Canterbury, with a response rate of 31.4 percent and 24.1 percent. The lower response rate from Canterbury may be due to the questionnaire's being sent out just once instead of three times at Otago. After cleaning the data, the final usable sample has 623 observations.

The dependent variable, Y, was constructed based on the students' responses of their current return intention, which is their return intention at the time of the survey. A four-category dependent variable was constructed, i.e., Definitely Return (*DR*), Probably Return (*PR*), Probably Not Return (*PNR*), and Definitely Not Return (*DNR*). Table 1 lists the assigned $Y = m$ for the four outcome categories, where $m = 1, 2, ..., J$ and $J = 4$.

Four sets of explanatory variables are used, as listed in Table 1. These sets of explanatory variables are selected based on the theoretical and empirical literature in general migration, brain drain and students' nonreturn. The first set of variables captures how individual and family demographics influence the students' return intention. As in most types of migration, skilled or unskilled, life-cycle and family considerations are always taken into account in making migration decisions (Greenwood 1985).

The set of education-related variables is particularly pertinent to studies on students. The literature points out that, students who are more likely to migrate or not return home, are those with higher levels of education, foreign-educated, and those specializing in relatively capital-dependent areas of study.

According to the human capital theory of migration originated by Sjaastad (1962), migration decisions take into account the expected or perceived costs and benefits associated with a move. In the context of this paper, students contemplating nonreturn would be taking into account work-related aspects such as wage compensation, skill use opportunities, and work environment. The current paper defines work environment as inclusive of high quality peers and adequate work resources (both financial and physical). Perceived costs and benefits would also be weighed in terms of social-related aspects such as lifestyle, family ties, and race equality.

Adapting from the seminal work of Bourdieu (1986) and the empirical studies by Waters (2006, 2007, 2009) and Zweigenhaft (1993), the fourth set of explanatory variables includes two variables to capture possible effects of cultural and social capital on return intention, i.e., (i) whether or not English is the students' native language (a proxy of cultural capital), and (ii) whether or not there is presence of formalized social groups from the same home country (a proxy of social capital).[2]

[2] Examples of formalized social groups in the University of Otago are the Otago Malaysian Students Association, the Indian Students Association, the Brunei Students Association, and the Indonesian Community Association. Waters (2007) also refers social capital as membership of a distinctive and self-referential social group.

Table 1. Variables' description

Variables	Description
A 4-category dependent variable	
1 = DNR	Definitely Not Return
2 = PNR	Probably Not Return
3 = PR	Probably Return
4 = DR	Definitely Return
4 sets of explanatory variables	
Set 1: Demographic and family-related variables	
age	Years of age
yrsinNZ	Years of stay duration/residence in New Zealand
workyrs	Years of work experience at home prior to current study
single	1 if single or not married; 0 otherwise
male	1 if male; 0 otherwise
initialreturn	1 if initially intend to return home, i.e., the return intention prior to coming to New Zealand for current study; 0 otherwise
supportive	1 if family is supportive of any nonreturn/migration intention; 0 otherwise
dadtertiary	1 if father has tertiary level education; 0 otherwise; a proxy of socioeconomic status
Set 2: Education-related variables	
phd	1 if a PhD student; 0 otherwise
abroad	1 if studied abroad before prior to current study; 0 otherwise; a proxy of mobility
science	1 if in the science discipline of study; 0 otherwise; base group
hscience	1 if in the health science discipline of study; 0 otherwise
humanities	1 if in the humanities discipline of study; 0 otherwise
commerce	1 if in the commerce discipline of study; 0 otherwise
Set 3: Home perception-related variables	
workenviron	1 if work environment is perceived good at home; 0 otherwise
wage	1 if wage competitiveness is perceived good at home; 0 otherwise
skilluse	1 if skill use opportunity is perceived good at home; 0 otherwise
lifestyle	1 if lifestyle is perceived good at home; 0 otherwise
familyties	1 if family/social ties is perceived good at home; 0 otherwise
equalrace	1 if race equality is perceived good at home; 0 otherwise
Set 4: Sociocultural-related variables	
english	1 if English is the native language of a home country; 0 otherwise
homegroup	1 if there is presence of a social group of a home country; 0 otherwise

Table 2 provides some descriptive statistics of the explanatory variables. On average, the students in the final sample are relatively young, at around 24 years old. They would have normally stayed in New Zealand for almost 3 years and would have slightly more than a year of work experience, on average. A disproportionately large number of the students are single or not married (90 percent). About two-thirds of the students come from privileged socio-economic background (‘dadtertiary’).[3]

[3] Appendix 1 shows the pairwise correlation matrix of all the explanatory variables. Some collinearity diagnostics are also provided in Appendix 2.

Table 2. Summary statistics

Variables	Mean	Std. Dev.	Min	Max	Mode
age	24.5	5.17	17	55	-
yrsinNZ	2.73	2.16	0.1	11.3	-
workyrs	1.29	2.93	0	18	-
single	0.90	0.30	0	1	1
male	0.48	0.50	0	1	0
phd	0.25	0.43	0	1	0
hselsewhr	0.45	0.50	0	1	0
science*	0.38	0.49	0	1	0
hscience	0.18	0.38	0	1	0
humanities	0.20	0.40	0	1	0
commerce	0.24	0.43	0	1	0
initialreturn	0.39	0.49	0	1	0
supportive	0.48	0.50	0	1	0
dadtertiary	0.65	0.48	0	1	1
workenviron	0.23	0.42	0	1	0
wage	0.37	0.48	0	1	0
skilluse	0.27	0.45	0	1	0
lifestyle	0.27	0.44	0	1	0
familyties	0.74	0.44	0	1	1
equalrace	0.36	0.48	0	1	0
english	0.24	0.43	0	1	0
homegroup	0.34	0.47	0	1	0

Note: ‘age’, ‘yrsinNZ’, and ‘workyrs’ are continuous variables in units of years, while the rest are dummy variables. Science is the base group for disciplines of study.

3 Partial proportional odds model

This paper examines how students choose among four alternatives or outcomes, i.e., Definitely Not Return (*DNR*; *Y*=1), Probably Not Return (*PNR*; *Y*=2), Probably Return (*PR*; *Y*=3) and Definitely Return (*DR*; *Y*=4). These four outcomes make up the 4-category or 4-outcome dependent variable, *Y*. The probabilities that *Y* is a particular m outcome category can be generally expressed as follows.

$$P(Y=1) = 1 - g(X\boldsymbol{\beta}_1)$$

$$P(Y=m) = g(X\boldsymbol{\beta}_{m-1}) - g(X\boldsymbol{\beta}_m) \qquad \text{for } m = 2, \ldots, J\text{-}1$$

$$P(Y=J) = g(X\boldsymbol{\beta}_{J-1}) \tag{1}$$

The 4-outcome dependent variable *Y* is the discrete counterpart of an underlying continuous latent variable Y^*, where Y^* takes a structural form of $Y^* = X\beta + \varepsilon$. Let Y^* represent the unobserved tendency or propensity to return. It is this unobserved propensity to return that governs a student’s observed (stated) return intention.

Given that the outcome categories of the dependent variable appear to be ordered in terms of the intensity of intention, a typical approach is to use the standard ordered logit model. The results from the standard ordered logit model would only be valid if the parallel lines assumption is met.[4] However, after fitting the standard ordered logit model, a formal test on the assumption reveals that it has been violated.[5] Therefore, the use of the standard ordered logit model would be inappropriate. This paper proposes the use of the partial proportional odds model.

There are three cases of the ordered logit model with respect to the imposition or relaxation of the parallel lines assumption (Williams 2006). The three cases are as follows.

(i) The proportional odds case (the most restrictive but most parsimonious case, i.e., the standard ordered logit model). It assumes that the parallel lines assumption holds for all m outcome categories, i.e., it assumes the same coefficient vector $\boldsymbol{\beta}$ for all m outcome categories.

(ii) The partial proportional odds case (i.e., the proposed model in this paper). It relaxes the parallel lines assumption for a subset of the $\boldsymbol{\beta}$ across m outcome categories.

(iii) The unconstrained case (the most flexible but least parsimonious case, i.e., the generalized ordered logit model).[6] It relaxes the parallel lines assumption for all m outcome categories, i.e., it allows $\boldsymbol{\beta}$ to differ for each of the m outcome categories (Long and Freese 2006).

Table 3 summarizes the position of the partial proportional odds model in relation to the parsimony in the number of parameters estimated and the flexibility of the parallel lines assumption. Table 3 shows that the partial proportional odds model compromises between the parameter parsimony and assumption flexibility features.

In the first extreme case, the standard ordered logit model, its cumulative probabilities are expressed as follows:

$$P(Y \le m \mid \boldsymbol{X}) = F(\tau_m - \boldsymbol{X\beta}) \quad \text{for } m = 1,2, \ldots, J \qquad (2)$$

[4] The ordered logit model can be viewed as a set of *J–1* cumulative binary logit equations (DeMaris 1992). The parallel lines assumption restricts the coefficients of each explanatory variable to be identical across the set of *J–1* cumulative equations. That is, in the case of the standard ordered logit model, it only estimates one set of coefficients to be used across all the *J–1* cumulative equations. In other words, the parallel lines assumption implies that $\boldsymbol{\beta}_1 = \boldsymbol{\beta}_2 = ... = \boldsymbol{\beta}_{J-1}$, where *1, 2, …, J–1* is the *m* outcome category. Any differences in the estimated coefficients should only be due to sampling variation. Therefore, if the parallel lines assumption holds, then the estimated coefficients $\widehat{\boldsymbol{\beta}}_1 = \widehat{\boldsymbol{\beta}}_2 = ... = \widehat{\boldsymbol{\beta}}_{J-1}$ should be identical or similarly close (Long and Freese 2006).

[5] Brant (1990) presents a formal test to determine which explanatory variables violate the parallel lines assumption. The Brant test is actually a Wald test which (i) allows an overall test that all $\boldsymbol{\beta}_m$'s are equal and (ii) tests the equality of coefficients for individual variables (Long 1997). The results of the Brant test are given in the following Section 4.

[6] The generalized ordered logit model may be regarded as the ordered counterpart of the multinomial logit model. However, the multinomial logit model is from the family of Generalized Extreme Value models (Train 2003), whereas the generalized ordered logit model is not.

Table 3. Position of the partial proportional odds model

	OLM	PPOM	GOLM
Parsimony in parameters	High	Medium	Low
Flexibility in assumption	Low	Medium	High

Note:
OLM: Ordered logit model
PPOM: Partial proportional odds model
GOLM: Generalized ordered logit model

In the other extreme case, the generalized ordered logit model, its cumulative probabilities are:

$$P(Y \leq m \mid \boldsymbol{X}) = F(\alpha_m - \boldsymbol{X\beta_m}) \text{ for } m = 1,2, \ldots, J \qquad (3)$$

The main difference between equations (2) and (3) is that the generalized model uses a different set of coefficients, $\boldsymbol{\beta}_m$, for each outcome category, instead of the same set of coefficients for all outcome categories, $\boldsymbol{\beta}$, as in the standard model. The τ and α terms are the cutpoints or threshold parameters used in the standard and generalized ordered logit model respectively.

In the partial proportional odds model, some of the $\boldsymbol{\beta}$ coefficients in equation (3) can be the same (or fixed) for all m outcomes, while some other $\boldsymbol{\beta}_m$ coefficients are allowed to differ by m outcomes. For example, say the $\boldsymbol{\beta}$s for the explanatory variables X_1 and X_2 are the same for all m outcomes and the $\boldsymbol{\beta}_m$ for variable X_3 are allowed to differ by outcome m. Then, equation (3) can be explicitly expressed as follows.

$$P(Y \leq m \mid \boldsymbol{X}) = F(\alpha_m - X_1\beta_1 + X_2\beta_2 + X_3\beta_{3m}) \text{ for } m = 1,2, \ldots, J \qquad (4)$$

By fitting the partial proportional odds model, the parallel lines assumption is then relaxed only for those explanatory variables that violate the assumption. The assumption is violated when there are different frames of reference in answering questions pertaining to one's return intention.

For instance, the frames of reference may not be the same even for students with the same favourable perceptions on a certain aspect of home. Different frames of reference as to how students perceive a certain aspect of home will in turn affect their unobserved inclinations of expressing a particular intention in different ways. Different frames of reference translate into shifting (different) cutpoints along the arbitrary continuous scale of the latent Y^* variable, i.e., the propensity to return. Shifting cutpoints are what violate the parallel lines assumption.

4 Results and discussions

This section discusses the results of the model's coefficient estimates, the odds ratios, the marginal effects, and the predicted outcome probabilities.

4.1 Results and discussion I: Coefficients and odds ratios

There are three result panels in Table 4, i.e., Definitely Not Return (DNR), Probably Not Return (PNR) and Probably Return (PR). The first panel contrasts the DNR category with the PNR, PR and DR categories. That is, the signs of the coefficients in the first panel imply how likely it is a student is to express a Definitely Not Return intention as opposed to the remaining three categories of intention.

Table 4. Coefficients and odds ratios

Variables	Coeff.	s.e.	Odds ratio	s.e.
Definitely Not Return (DNR)				
age	0.0067	0.0275	1.0068	0.0277
yrsinNZ	**-0.1150****	**0.0472**	**0.8913**	**0.0420**
workyrs	0.0318	0.0424	1.0323	0.0438
single	0.3108	0.3004	1.3645	0.4100
male	-0.1340	0.1634	0.8746	0.1429
phd	**-0.4075***	**0.2344**	**0.6653**	**0.1559**
abroad	0.1493	0.1899	1.1611	0.2204
hscience	**-0.5717****	**0.2418**	**0.5646**	**0.1365**
humanities	-0.2380	0.2319	0.7882	0.1828
commerce	**-0.3726***	**0.2126**	**0.6890**	**0.1465**
initialreturn	**1.7555*****	**0.1839**	**5.7864**	**1.0639**
supportive	**-0.5130*****	**0.1627**	**0.5987**	**0.0974**
dadtertiary	0.1408	0.1678	1.1512	0.1932
workenviron	**0.3940***	**0.2075**	**1.4829**	**0.3076**
wage	-0.4572	0.3063	0.6331	0.1939
skilluse	**0.7853***	**0.4069**	**2.1930**	**0.8923**
lifestyle	-0.0086	0.3624	0.9914	0.3593
familyties	**0.5920*****	**0.1955**	**1.8077**	**0.3534**
equalrace	0.2623	0.1788	1.3000	0.2325
english	0.1813	0.2082	1.1987	0.2496
homegroup	-0.0517	0.1902	0.9496	0.1807
Probably Not Return (PNR)				
wage	0.2628	0.2185	1.3005	0.2842
skilluse	**0.8289*****	**0.2325**	**2.2907**	**0.5327**
lifestyle	**1.1329*****	**0.2394**	**3.1048**	**0.7432**
Probably Return (PR)				
wage	0.3970	0.2626	1.4873	0.3906
skilluse	**1.4641*****	**0.2557**	**4.3237**	**1.1057**
lifestyle	**0.7426*****	**0.2576**	**2.1014**	**0.5413**

Note: DNR = Definitely Not Return ($Y=1$); PNR = Probably Not Return ($Y=2$); PR = Probably Return ($Y=3$); DR = Definitely Return ($Y=4$). Significant at *10%, **5%, ***1% level. s.e. = standard errors.

Similarly, the second panel contrasts the DNR and PNR categories with the PR and DR categories. The third panel contrasts the DNR, PNR and PR categories with the DR category. Each panel gives the results for two versions of the estimates, i.e., in coefficients and the odds ratio estimates.

Altogether, the model estimates 27 coefficients, i.e., 21 in the first panel, and three each in the remaining two panels. The coefficients and odds ratios that are left out in the last two panels are identical to those in the first panel. The three variables (i.e., wage, skilluse, lifestyle) in the last two panels are the variables that were found to violate the parallel lines assumption.[7] The partial proportional odds model therefore allows the coefficients of these three variables to vary across the J–1 equations.[8]

In interpreting the results of each panel in Table 4, the current category and lower-coded categories are taken as the base group. That is, the results in the m^{th} panel are equivalent to those of a binary logit model where categories 1 to m are coded as zero (as the base group) and categories m+1 to J are coded as one. Therefore, positive coefficients or odds ratios greater than 1, imply that higher values of an explanatory variable increase the probability that a student is in a higher category of Y than the current one. Negative coefficients or odds ratios less than 1, imply that higher values of an explanatory variable increase the probability of being in the current or a lower category (Williams 2006). For example, the positive coefficient of 0.8289 for the variable 'skilluse' in the second panel indicates that a student with favourable perceptions on skill use opportunities at home would be more likely to express a *PR* or a *DR* intention than a *DNR* or *PNR* intention.

For the three variables that do not meet the parallel lines assumption, their coefficient estimates and odds ratios differ in each panel. The first panel shows that a student who perceives favourably skill use opportunities at home is 2.19 times more likely to express a *DR*, PR or *PNR* intention than a Definitely Not Return intention. The second panel shows that he is 2.29 times more likely to express a *DR* or *PR* intention than a *DNR* or *PNR* intention. Similarly, the third panel shows that the student is 4.32 times more likely to express a Definitely Return intention than other intention categories.

4.1 Results and discussions II: Marginal effects

Table 5 presents the marginal effects which are computed at a representative value, i.e., at the mean values of continuous variables and mode values of dummy variables. Table 5 shows that in general, the marginal effects have larger magnitudes of impact on the two middle outcomes, Probably Not Return and Probably Return, and smaller impact on the extreme outcomes, Definitely Not Return and Definitely Return.

Table 5 shows that initial return intention variable has the largest magnitude of marginal impact on the outcome probabilities. A student who initially intends to return sees a larger increase in the probability of having a Probably Return intention, i.e., an increase by about 21 percent, while the probability of having a Definitely Return intention increases by a slightly lower 18 percent. Past empirical studies on similar

[7] The Brant test reveals that the perceptions on home wage competitiveness, skill use opportunities, and lifestyle violate the parallel lines assumption. Their chi-square statistics are 9.40, 7.83, and 10.91 respectively and their corresponding p-values reject the null hypothesis of parallel lines at the five percent significance level.

[8] Had a standard ordered logit model been estimated, then there would just be 21 estimated coefficients, i.e., one for each explanatory variable, assumed to be the same across the $J–1$ equations. Had a generalized ordered logit model been estimated, then there would be $21\times3=63$ estimated coefficients, i.e., a different set of coefficients for each of the $J–1$ equations.

Table 5. Marginal effects

	Definitely Not Return (DNR)		Probably Not Return (PNR)		Probably Return (PR)		Definitely Return (DR)	
variable	MER	s.e.	MER	s.e.	MER	s.e.	MER	s.e.
age	-0.0004	0.0018	-0.0012	0.0049	0.0013	0.0054	0.0003	0.0013
yrsinNZ	**0.0074***	**0.0040**	**0.0204****	**0.0084**	**-0.0224****	**0.0093**	**-0.0053****	**0.0024**
workyrs	-0.0020	0.0027	-0.0056	0.0077	0.0062	0.0083	0.0015	0.0021
single	-0.0229	0.0253	-0.0495	0.0444	0.0598	0.0569	0.0125	0.0114
male	0.0091	0.0113	0.0228	0.0283	-0.0261	0.0318	-0.0058	0.0074
phd	0.0313	0.0205	**0.0623***	**0.0371**	**-0.0778***	**0.0445**	-0.0158	0.0099
abroad	-0.0090	0.0116	-0.0275	0.0353	0.0291	0.0370	0.0074	0.0097
hscience	**0.0472***	**0.0253**	**0.0807****	**0.0368**	**-0.1072****	**0.0442**	**-0.0206****	**0.0099**
humanities	0.0170	0.0175	0.0390	0.0380	-0.0461	0.0448	-0.0099	0.0099
commerce	0.0282	0.0178	**0.0578***	**0.0350**	**-0.0714***	**0.0408**	-0.0146	0.0093
initialreturn	**-0.0565*****	**0.0178**	**-0.3352*****	**0.0342**	**0.2119*****	**0.0635**	**0.1798*****	**0.0455**
supportive	**0.0412*****	**0.0162**	**0.0746****	**0.0312**	**-0.0969*****	**0.0316**	**-0.0190****	**0.0084**
dadtertiary	-0.0096	0.0118	-0.0239	0.0287	0.0274	0.0326	0.0061	0.0075
workenviron	**-0.0215***	**0.0114**	**-0.0760***	**0.0432**	**0.0756***	**0.0387**	0.0219	0.0150
wage	0.0359	0.0266	**-0.1005****	**0.0503**	0.0426	0.0507	0.0220	0.0159
skilluse	**-0.0364****	**0.0178**	**-0.1678*****	**0.0531**	0.0717	0.0618	**0.1325*****	**0.0438**
lifestyle	0.0006	0.0235	**-0.2741*****	**0.0478**	**0.2251*****	**0.0543**	**0.0484****	**0.0242**
familyties	**-0.0493****	**0.0214**	**-0.0826****	**0.0341**	**0.1107*****	**0.0363**	**0.0212****	**0.0092**
equalrace	-0.0151	0.0110	-0.0494	0.0345	0.0508	0.0347	0.0137	0.0102
english	-0.0108	0.0123	-0.0336	0.0396	0.0353	0.0404	0.0091	0.0112
homegroup	0.0034	0.0126	0.0090	0.0332	-0.0101	0.0371	-0.0023	0.0086

Note: Significant at the *10%, **5%, and ****1% level. MER = Marginal effects computed at a representative value, i.e., at mean values of continuous variables and mode values of dummy variables. s.e. = standard errors students' nonreturn intention using initial intention as an explanatory variable have also found its marginal impact to be highly significant (Gungor and Tansel 2008; Zweig 1997). Due to the large marginal effect magnitude of the initial return intention variable, there may be concern that it may be essentially measuring the same thing as the dependent variable (the current return intention). However, the simple correlation between initial intention and current intention is quite low at 0.45.[9]

The probability of having a Probably Not Return intention is, on average, 6.2 percent more for a doctoral student. Conversely, the probability of having a Probably Return intention is, on average, 7.8 percent lower for such students. Although the impact is only significant on these two outcomes, the results nevertheless lend some empirical support to the hypothesis that doctoral students are less likely to return. This may be due to the nature of the doctoral degree, where students typically engage in research that has less practical relevance in their home countries (Lien 1988), hence their reluctance to return.

According to Lien (1988), misdirected R&D efforts might have counter-productive effects of inducing even more educated people to avoid returning home. Lien focuses specifically on academic research which is most relevant in the brain drain and students' nonreturn context. Lien categorizes such academic research into two types, high-income and low-income type of research, which are most relevant and useful to the developed and developing countries respectively.
More often than not, students studying in developed countries are engaged in the high-income type of research, which would have few relevant applications at home, especially if home is a developing country.[10] Due to its limited applications, students skilled in high-income type of research may not be valued highly at home. In this case, Lien hypothesizes that such students, particularly those at the level of doctoral studies, are less likely to return home.

There is perhaps another plausible explanation as to why foreign students, particularly those at the doctoral level, are found to be less likely to return. According to Bratsberg (1995), if a home country values more of the skills acquired by their students while abroad than a host country does, students are more likely to return. Such valuation of skills is manifested through a recently intense global competition in attracting talent, in which there appears to be a tug-of-war between host countries trying to retain highly skilled foreign students and home countries trying to attract them home (Kuptsch 2006; Ziguras and Law 2006).

There are significant impacts on the probability of having either a Probably Not Return or a Probably Return intention for a student from the commerce discipline. Commerce students, compared with science students, are less likely to

[9] Note that the initial intention refers to the return intention of a student before he (or she) comes to New Zealand. However, due to practicality, a student is asked of his initial intention only after he is in New Zealand. The initial return intention can be regarded as a lagged dependent variable, where such a variable is used to account for factors that cause *current* differences in the dependent variable that are difficult to account for in other ways and to capture inertial effects (Wooldridge 2009; italic emphasis is Wooldridge's). It acts as a proxy variable of those factors (unobserved) which would have otherwise be unaccounted for (Kennedy 2008). There is of course a risk of endogeneity in including the initial return intention as one of explanatory variables. However, as shown in Section 5, statistical evidence suggests the initial return intention to be exogenous.

[10] This paper does not include a dummy of country type (i.e., either developed or less developed country) as one of the explanatory variables as it is highly insignificant. Furthermore, the country type would have been captured by the perception-related variables.

return home. Likewise, health science students are also less likely to return home, compared with science students.[11] The syllabus structure of the commerce and health science programs in New Zealand offers some plausible explanation of why such students are less inclined to return home. These students acquire knowledge which may apply only to New Zealand and may not be transferable, especially back to less developed home countries.

For example, health science students may not be appropriately trained to deal with health issues that only exist in less developed countries. Furthermore, from the perspective of a host country, it is preferable to retain these students as future health workforce than to import foreign-trained health workers whom may not be well-trained and may deliver inferior health services (Legrain 2006).

Hence, if a host country plans to retain its foreign students, the curriculum can be changed accordingly to cater for the needs of the host country. This would result in, to an extent, less transferable knowledge and subsequently the reluctance to return home.

The results here also partially support Chen and Su's (1995) hypothesis that students from capital-dependent disciplines are less likely to return home. They define a capital-dependent discipline as a discipline with relatively large stock of both physical and human capital, where such capital is country-specific. A higher capital stock contributes to higher marginal productivity of skills. Students studying in a capital-dependent discipline would be less motivated to return home if the capital stock at home is not comparable with those of the host country. For the purpose of testing their hypothesis, it is plausible to assume that the science and health science disciplines are relatively more capital-dependent than the commerce and humanities disciplines.

Students who have good perceptions of the work environment at home are more likely to return. For students with such perceptions, the probability of having a Definitely Not Return intention and the probability of having a Probably Not Return intention decreases while the probability of having a Probably Return intention increases. However such good perceptions do not have any significant effect on the probability of having a Definitely Return intention. Nevertheless, the results here lend some empirical support to Miyagiwa's (1991) agglomeration hypothesis. Miyagiwa hypothesizes that an individual is more productive if he works in close proximity with high quality peers. When there are more of such individuals, it will create a more amenable environment for productivity to thrive on.

Favourable perceptions of wage competitiveness at home have a significant negative impact on the probability of having a Probably Not Return intention, where this probability decreases by about 10 percent for students who view wage to be competitive at home. Favourable perceptions of wage at home may still induce students to return though its effects are considerably less than those of the perceptions of skill use opportunities and lifestyle at home.

Good perceptions of lifestyle and family ties at home also have large and significant impact on a student expressing either a Probably Not Return or a Probably Return intention. The findings here on the perceptions of wage, lifestyle and family ties, seem consistent with those found by Gibson and McKenzie (2009) where they conclude that return decisions are strongly related to family and lifestyle factors, rather than to the income factor.

[11] The level of study was interacted with the different disciplines of study, but the interaction terms were highly insignificant, and are therefore excluded from the final model.

Table 5 shows that good perceptions of skill use opportunity at home have the largest positive impact on the probability of a student expressing a Definitely Return intention, i.e., increasing the probability by about 13 percent. This is an encouraging finding for home countries, because it implies that students are more likely to return if there are enough opportunities for them to use their newly acquired skills.

Most of the demographic variables are found to be insignificant. This may be due to the lack of variation in the demographics of the students, where the majority of the students are single, have no work experience and have an average age of 24.

Table 5 also shows that the two variables, 'english' and 'homegroup', are insignificant in their effects on the students' return intention. This may be because foreign students doing degree courses in New Zealand would most probably have already had an acceptable level on their command of English, so that language makes no difference in their return intention. As for the insignificant effect of the presence of home social groups, it may be that foreign students would prefer to mingle with those from other countries so as to maximize their experience with people from different cultures. Hence, the presence of social groups from the same home country makes no difference in their return intention.

4.1 Results and discussions III: Outcome probabilities

While the preceding section examines by how much the outcome probabilities change due to changes in an explanatory variable, this section looks at what the outcome probabilities are when there is a change in a variable or a subset of variables.

Table 6 shows eight scenarios with Scenario 1 as the baseline scenario, against which other scenarios may be compared with. Each scenario represents a hypothetical student with characteristics as listed. A student with characteristics as depicted in the base scenario observes the highest probability of having a Probably Not Return intention, i.e., Pr(Y=PNR)=0.5233. The outcome probabilities in the base scenario are computed at the mean values of continuous variables and mode values of dummy variables.

Scenario 2 depicts a student who has favourable perceptions of all of her home country's attributes, while her other characteristics remain the same as in Scenario 1. A student with such good perceptions of home is about 10 times more likely to have a definite return plan than a student with only favourable perception of family ties at home, i.e., Pr(Y=DR)=0.5714 of Scenario 2 versus Pr(Y=DR)=0.0487 of Scenario 1.

In contrast, Scenario 3 depicts a student who has only unfavourable perceptions on all the six aspects of her home country. Scenario 3 now sees the student's probability of having a definite return plan drops drastically from Pr(Y=DR)=0.5714 in Scenario 2 to Pr(Y=DR)=0.0275 in Scenario 3.

Let us compare Scenario 2 and 3. The probability of expressing a Definitely Not Return intention in Scenario 3 is Pr(Y=DNR)=0.1184. Now, we would expect this probability to be a somewhat mirror image of Scenario 2's Pr(Y=DR)=0.5714 since the only difference between Scenario 2 and 3 lies in the six home attributes. The large disparity between Scenario 2's Pr(Y=DR)=0.5714 and Scenario 3's Pr(Y=DNR)=0.1184 suggests that unfavourable perceptions of home attributes (as depicted in Scenario 3) are not as strong as a determinant in influencing the probability of having a Definitely Not Return intention, as compared to favourable perceptions of home attributes (as depicted in Scenario 2) in influencing the

Table 6. Outcome probabilities

	Scenarios							
Variables	1	2	3	4	5	6	7	8
age	24.5				35			
single	1				0			
male	0							
yrsinNZ	2.7			5	1			
workyrs	1.3			0	5			
phd	0			1	1			
abroad	0							
hscience	0							
humanities	0							
commerce	0							
initialreturn	0				1			
supportive	0							
dadtertiary	1							
workenviron	0	1			1			
wage	0	1			1	1		
skilluse	0	1			1		1	
lifestyle	0	1			1			1
familyties	1		0	0				
equalrace	0	1			1			
english	0							
homegroup	0							
Predicted outcome probabilities								
Pr(Y=DNR)	0.0692	0.0273	0.1184	0.2146	0.0067	0.1051	0.0328	0.0697
Pr(Y=PNR)	0.5233	0.0481	0.6059	0.6278	0.0125	0.4227	0.3554	0.2492
Pr(Y=PR)	0.3589	0.3532	0.2481	0.1439	0.1337	0.4015	0.4306	0.5840
Pr(Y=DR)	0.0487	0.5714	0.0275	0.0137	0.8471	0.0707	0.1812	0.0971

Note: Scenario 1 is the baseline scenario where continuous variables are held at mean values while dummy variables at mode values.

probability of having a Definitely Return intention.

Scenario 4 depicts a student who furthers into her doctoral studies immediately from her undergraduate studies. A student with the characteristics depicted in Scenario 4 would typically have stayed in New Zealand for a number of years and has no work experience. Scenario 4 further assumes that this student has no good perceptions of home. For such a student, her probability of having a definite migration plan is Pr(Y=DNR)=0.2146.

Scenario 5 is a contrast of Scenario 4. Scenario 5 depicts a mature and married student who has had some work experience prior to her current studies. She has been staying in New Zealand for a year and her initial intention has been to return home after completing her studies. Furthermore, she has only good perceptions of her home country. In this case, she is very likely to have a definite return plan, at Pr(*Y*=*DR*)=0.8471. Furthermore, her probability of having a definite migration plan is almost nonexistent, at Pr(*Y*=*DNR*)=0.0067.

The last three scenarios 6 to 8 show the effect of the individual variable: wage, skilluse, and lifestyle. Contrary to the received wisdom from the literature, good perceptions of wage competitiveness at home do not have as large an impact as that of good perceptions of skill use opportunities and lifestyle. For example, a good perception of home wage increases the probability of having a Probably Return intention from 0.3589 (in the baseline scenario) to only 0.4015 (Scenario 6), whereas a good perception on home lifestyle increases the probability of having a Probably Return intention from 0.3589 to 0.5840 (Scenario 8). The evidence here suggests that other aspects of home may be more important than wage competitiveness in influencing return intentions.

5 Model specification tests

This section checks for the adequacy of the partial proportional odds model in terms of how well the model fits the data. These tests, as listed in Table 7, are imperative as an inappropriately specified model leads to misleading inferences.

The Wald chi-square test is a test of the partial proportional odds model's overall goodness-of-fit. It tests for the null hypothesis that all the coefficients in the model are simultaneously equal to zero, i.e., having no effect on the dependent variable. This test is the nonlinear counterpart of the linear regression model's F-test. The significant p-value as shown in Table 7 indicates that the null hypothesis is strongly rejected, i.e., at least one of the coefficients in the model has an impact on return intention.

The general model specification test, also known as a link test, is a test of appropriate functional form of the model. This test is the nonlinear counterpart of Ramsey's (1969) RESET test for linear regression models. If a model is properly specified, then no nonlinear functions of the explanatory variables, such as the quadratic function, should be significant when added to the model. Here, the nonlinear functions of the explanatory variables are represented by the '_hatsq' variable. This variable is tested insignificant for each *J*–1 equation, i.e., the insignificant p-values. This indicates no functional form misspecification.

Table 7. Model specification tests

Tests	Results
Wald chi-square test	*p*-value = 0.000
General model specification test	
i. DNR: _hatsq	*p*-value = 0.395
ii. PNR: _hatsq	*p*-value = 0.747
iii. PR: _hatsq	*p*-value = 0.785
Threshold parameter test	
i. Alpha_1	*p*-value = 0.030
ii. Alpha_2	*p*-value = 0.083
iii. Alpha_3	*p*-value = 0.000
Exogeneity test on 'initialreturn' variable	*p*-value = 0.241
Percent correctly predicted (PCP)	PCP = 55.54%

As mentioned in Section 3, the alpha terms in a partial proportional odds model are cutpoints or threshold parameters along the continuum of the unobserved propensity to return. With four outcome categories, there are three cutpoints to be tested. The results of the threshold parameter test indicate that the three cutpoints (Alpha_1 to Alpha_3) are significant at the 10 percent significance level. That is, the three cutpoints are relevant to the model, indicating that the four observed outcome categories are indeed ordinal in nature and are well-placed along the continuous scale of the unobserved propensity to return. The significant cutpoints also suggest that the four outcome categories should not be collapsed into three or less categories.

Using Smith and Blundell (1986) exogeneity test, there is no statistical evidence that the initial return intention is endogenous.[12] In this test, the null hypothesis is that the model is appropriately specified with all the explanatory variables as exogenous. The null hypothesis is tested against the alternative hypothesis that the residuals from regressing the suspected endogenous variable on a set of instruments would have explanatory power on the dependent variable. An insignificant p-value of 0.241 here indicates that the residuals do not have any explanatory power, suggesting the initial return intention to be exogenous.

The percentage correctly predicted (*PCP*) statistic, calculated from a classification or hit-miss table, summarizes the predictive power of the model. The *PCP* statistic is a measure of how well the model can predict the actual observed outcome. The *PCP* of 55.54 percent here means that the partial proportional odds model correctly classifies about 56 percent of the outcomes.

Earlier in the introduction section, this paper pointed out that the use of a partial proportional odds model is a departure from the norm in the students' nonreturn literature, which usually employs an ordered or a multinomial regression model. Here, we estimate and compare the goodness-of-fit measures (the Akaike's Information Criterion or *AIC*) of a partial proportional odds (*AIC*=1343.17), an ordered logit (*AIC*=1353.36), and a multinomial logit model (*AIC*=1379.52). The *AIC* measures provide some statistical evidence that the

[12] To test for any potential endogeneity of the initial return intention variable, it is instrumented with a dummy of whether or not a student is self-financed. A valid instrument fulfils two conditions, the instrument relevance and exogeneity conditions. According to Wooldridge (2009), the easiest way to test the instrument relevance condition is to estimate a simple regression between the suspected endogenous variable and the instrument. Therefore, the initial return intention is regressed (using a simple logit regression) on the self-financed dummy as the sole explanatory variable. The results of the simple regression show that the self-financed dummy is significant at the 5% significance level in explaining initial return intention. The instrument relevance condition is met, i.e., there is correlation between the potentially endogenous variable (the initial intention variable) and the instrument (the self-financed dummy variable). The instrument exogeneity condition however, cannot be tested. Here, it is argued that whether or not a student is self-financed should have a direct bearing on a student's initial return intention. Both these variables are found to be negatively correlated, suggesting that a self-financed student is more likely to have an initial intention of not returning home. This negative relationship seems plausible. Self-financed students may have such nonreturn initial intentions in order to recoup the cost of their self-financed education by exploring working opportunities abroad. There is also no a priori reason why the self-financed dummy variable should be correlated with the outcome variable (current return intention); furthermore, a simple pairwise correlation between these two variables reveals that the magnitude of the correlation coefficient, 0.0141, is negligible.

partial proportional odds model has the best fit, since a model with the smaller AIC is considered the better fitting model.[13]

The model specification tests in this section suggest that the partial proportional odds model fits the data reasonably well. The model is also checked for its robustness to changes in different model specifications and different functional forms of the explanatory variables. The results (unreported here) show that the partial proportional odds model can be regarded as reasonably robust as conclusions from key variables remain largely the same.[14]

6 Conclusion

This paper has looked into the determinants of the return intention of foreign students studying in tertiary-level courses in New Zealand universities. The results generally show that most of the factors have the largest impact on the Probably Not Return and Probably Return intention. The impact of the factors is relatively weaker on the Definitely Return and Definitely Not Return intention. In general, the set of home perception-related variables has larger impact on return intention than other explanatory variables. The results also reveal that having an initial intention to return and having good perceptions of skill use opportunities at home are the two factors that have the largest positive impact on the probability of having a Definitely Return intention.

While not much could be done with a student's initial return intention itself, perhaps the home country could ensure that a student does not have to leave home for tertiary education. Students might go for abroad studies due to insufficient supply of tertiary education at home or the lack of quality tertiary education at home. Home countries should look into the supply and quality of tertiary education at home, so that students do not have to leave home unnecessarily, and any initial ideas of whether or not to return home would not have existed in the first place. Such measures taken by home countries in reducing their students' outflows are recognized as part of the retention policy option (Gribble 2008). Alternatively, home countries could foster a sense of national allegiance through unity-building programmes such as Singapore's and Malaysia's compulsory national service required from youths prior to their university years. The use of patriotic conditioning has long been recognized as an approach to curb brain drain (Patinkin 1968).

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[13] Recall that the partial proportional odds model is used as it takes into account the ordinality of the dependent variable and it is not as restrictive as the ordered logit model in terms of the parallel lines assumption. Also, if the ordinality assumption of the dependent variable is indeed true, then the partial proportional odds model would better suit the data than the multinomial logit model. Therefore, in this sense and apart from the AIC criterion, the partial proportional odds model seems to be the best model.

[14] The robustness check or sensitivity analysis includes estimating a standard ordered logit model, a stereotype logit model (see Anderson 1984), a continuation ratio model (see Fienberg 1980), a model with the squared terms of the continuous explanatory variables, and a model with the interaction terms between the level and discipline of study. The coefficient estimates of these models are compared with those of the partial proportional odds model for changes in coefficient signs and significance levels. The standard ordered logit model, stereotype logit model, and continuation ratio model are compared to the partial proportional odds model because they all take into consideration the ordinal nature of the dependent variable (see Long and Freese 2006). Note that these three models were estimated to compare and assess the robustness of the partial proportional odds model, not its goodness-of-fit.

Since the perception of skill use opportunities is one of the factors having the largest positive impact on the Definitely Return intention, home countries should ensure enough opportunities for returning students to apply their newly acquired skills. There should be creation of jobs commensurate with the tertiary-level qualification of returning students. For such jobs to mushroom, the economy should be managed in such a way that it will not stagnate.

On the other hand, a host country can engage in some retention policies to retain its foreign students. Such policies can be aimed particularly at students who are reluctant to return home. In New Zealand, since November 2007, foreign students graduating from courses that are recognized under the Skilled Migrant Category are eligible for a 12-month Graduate Job Search permit, where previously it had only been a 6-month permit. For students who do not intend to return home, a longer duration for job search will increase the chances of landing a job commensurate with their tertiary qualification and subsequently the probability of staying on in New Zealand.

The paper also finds that studying in relatively more capital-dependent disciplines would make a student less likely to return. Perhaps the government should ensure that the physical capital used in capital-dependent sectors at home is on par with the physical capital used internationally. Students trained abroad will find it easier to transfer their knowledge back home when the physical capital at home is similar with those abroad. As for human capital, there should be effort to increase its level, as in for example, Malaysia's bid to produce 60,000 doctoral holders by the year 2015 under its MyBrain15 programme. Having such critical masses of quality peers at home will attract return due to agglomeration of human capital (Miyagiwa 1991).

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Appendix 1: Correlation matrix

	age	yrsinNZ	workyrs	single	male	phd	abroad
age	1.0000						
yrsinNZ	-0.1765	1.0000					
workyrs	0.7079	-0.2885	1.0000				
single	-0.4494	0.1091	-0.4327	1.0000			
male	0.0380	0.0592	0.0249	-0.0838	1.0000		
phd	0.5713	-0.1251	0.3202	-0.2891	0.0174	1.0000	
abroad	-0.2579	0.4737	-0.1627	0.1211	0.0327	-0.1213	1.0000
hscience	-0.0821	0.0873	-0.0634	-0.0247	0.0580	-0.0529	0.0515
humanities	0.0519	-0.1261	0.0523	-0.0285	-0.2293	-0.0683	-0.0967
commerce	0.0327	0.1084	0.0684	-0.0104	0.0244	-0.0529	0.0723
initialreturn	0.0637	-0.0715	0.1096	-0.0385	-0.0116	-0.0368	-0.0514
supportive	0.0069	0.0795	-0.0013	0.0484	-0.0608	-0.0495	0.0857
dadtertiary	-0.0917	0.0306	-0.1046	0.0330	-0.0184	-0.0399	0.0337
workenviron	0.0565	0.0141	0.0474	-0.0081	0.0465	0.0346	-0.0602
wage	0.2005	-0.0479	0.1361	-0.0291	-0.0432	0.0917	-0.1458
skilluse	0.0145	0.0738	0.0208	0.0273	0.0087	-0.0356	0.0011
lifestyle	-0.0472	0.0149	-0.0409	-0.0001	0.0119	-0.0212	0.0472
familyties	0.1558	-0.1584	0.1273	-0.0631	-0.0034	0.0388	-0.1705
equalrace	-0.1397	0.2368	-0.0781	0.0537	0.0661	-0.1228	0.1438
english	0.2142	-0.3458	0.2261	-0.0975	-0.0883	0.0776	-0.2522
homegroup	-0.1613	0.1230	-0.0867	0.0509	0.0414	-0.1306	0.1039

	hscience	humanities	commerce	initialreturn	supportive	dadtertiary	workenviron
hscience	1.0000						
humanities	-0.2356	1.0000					
commerce	-0.2622	-0.2850	1.0000				
initialreturn	0.0162	0.0463	0.0057	1.0000			
supportive	0.0604	0.0433	-0.0579	-0.0613	1.0000		
dadtertiary	0.0866	0.0371	-0.0827	-0.0022	0.0450	1.0000	
workenviron	-0.1130	0.0195	0.0699	0.0302	-0.0140	-0.0587	1.0000
wage	-0.1403	0.0900	-0.0048	0.0155	-0.0264	0.0685	0.3117
skilluse	-0.1078	0.0102	0.1668	0.1371	-0.0856	0.0138	0.2832
lifestyle	0.0101	0.0157	0.0723	0.1836	-0.0828	0.0287	0.2130
familyties	-0.0239	-0.0217	0.0904	0.2273	-0.0473	-0.1000	0.0479
equalrace	0.0849	-0.1083	0.0749	0.1179	-0.0705	-0.0134	0.0675
english	-0.1052	0.1810	-0.1064	0.0288	-0.0054	-0.0119	0.1594

homegroup	0.3188	-0.0623	-0.1447	0.0018	0.0592	-0.0246	-0.1819

	wage	skilluse	lifestyle	familyties	equalrace	english	homegroup
wage	1.0000						
skilluse	0.1906	1.0000					
lifestyle	0.0427	0.1531	1.0000				
familyties	0.0253	0.1063	0.1502	1.0000			
equalrace	-0.1161	0.0521	0.1734	0.0920	1.0000		
english	0.2517	0.0659	-0.0038	0.0475	-0.1360	1.0000	
homegroup	-0.3431	-0.1021	-0.0567	-0.0178	0.0263	-0.2397	1.0000

Appendix 2: Collinearity diagnostics

	VIF	Tolerance
age	3.14	0.32
yrsinNZ	1.55	0.64
workyrs	2.37	0.42
single	1.33	0.75
male	1.08	0.92
phd	1.62	0.62
abroad	1.43	0.70
hscience	1.28	0.78
humanities	1.36	0.74
commerce	1.35	0.74
initialreturn	1.12	0.89
supportive	1.06	0.95
dadtertiary	1.05	0.95
workenviron	1.25	0.80
wage	1.23	0.81
skilluse	1.18	0.85
lifestyle	1.15	0.87
familyties	1.16	0.86
equalrace	1.17	0.85
english	1.32	0.76
homegroup	1.32	0.76

Note: Mean VIF is 1.43.